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**LIQUIDITY AND COUNTERPARTY RISKS TRADEOFF
IN MONEY MARKET NETWORKS**

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Liquidity and Counterparty Risks Tradeoff in Money Market Networks¹

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Abstract

We examine how liquidity is exchanged in different types of Colombian money market networks (i.e. secured, unsecured, and central bank's repo networks). Our examination first measures and analyzes the centralization of money market networks. Afterwards, based on a simple network optimization problem between financial institutions' mutual distances and number of connections, we examine the tradeoff between liquidity risk and counterparty risk. Empirical evidence suggests that different types of money market networks diverge in their centralization, and in how they balance counterparty risk and liquidity risk. We confirm an inverse and significant relation between counterparty risk and liquidity risk, which differs across markets in an intuitive manner. We find evidence of liquidity cross-underinsurance in secured and unsecured money markets, but they differ in their nature. Central bank's role in mitigating liquidity risk is also supported by our results.

Keywords: liquidity risk, counterparty risk, network, centralization, money market

JEL codes: D85, E58, L14

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1 Introduction

During the global financial crisis of 2007-08 liquidity risk and counterparty risk increased rapidly as liquidity was rationed amid financial institutions' weakening (see Acharya et al. (2012), Acharya and Merrouche (2013), Abbassi et al. (2015), and Temizsoy et al.(2015)). As financial institutions became reluctant to engage in credit exposures, they started exchanging liquidity with the central bank. As a result, central bank borrowing facilities became an essential source of liquidity for financial institutions (Gale & Yorulmazer, 2013), which alleviated tensions in the money market, and avoided widespread contagion. Understanding the relationship between liquidity risk and counterparty risk, a long-lived issue in related literature, has gained importance since then.

Under the well-grounded notion that financial markets are among many other complex adaptive systems that may be better understood by means of network analysis (see Holland (1998), Sornette (2003), Haldane (2009), and Farmer et al. (2012)), we examine the connective structure of different types of money market networks in the Colombian case. Our examination is aimed at how liquidity is exchanged in the three markets that constitute the Colombian money market, namely secured and unsecured between financial institutions, and secured between financial institutions and the central bank. Such examination provides new insights about the tradeoff between liquidity risk and counterparty risk in money markets, corresponding to the tradeoff between the risk of being unable to find counterparties willing to provide liquidity and the risk of being unable to collect liquidity refunds, respectively.

Our examination is based on measuring the centralization (Freeman, 1979) of different types of money market networks, and on exploring how such centralization is related to the tradeoff between counterparty risk and liquidity risk. Regarding centralization, we illustrate how the two extreme cases of network centralization (i.e. *star* and *complete* networks) may be explanatory about the different connective structures money markets may exhibit, and about their main economic properties.

Regarding counterparty risk, based on recent research on the effects of connectedness in financial networks (see Battiston et al. (2012a) and Roukny et al. (2013)), we suggest that

under plausible conditions (e.g. market illiquidity, heterogeneous allocation of robustness) a complete network may be considered an extreme case of credit risk exposure that financial institutions avoid by establishing a few dedicated lending relationships (see Cocco et al. (2009), Afonso et al. (2013), and Temizsoy et al. (2015)). As in Castiglionesi and Wagner (2013) and Castiglionesi and Eboli (2015), counterparty risk and systemic risk, in the form of the costs of non-refunded liquidity and indirect contagion, respectively, deter financial institutions from providing liquidity insurance to all other financial institutions, and creates incentives for a sparse money market network in the form of underinsurance. This supports well-documented stylized facts of financial networks, namely their sparse, inhomogeneous, and clustered architecture (see Boss et al. (2004), Soramäki et al. (2007), Battiston et al. (2012b), Craig and von Peter (2014), in 't Veld and van Lelyveld (2014), and León and Berndsen (2014)), though it contradicts the theoretical model of Allen and Gale (2000), which argues that complete networks diversify counterparty risk under strict and unrealistic assumptions (e.g. complete information, complete markets, perfect competition, and agents' homogeneity and identical behavior).⁴ On the other hand, as it has been put forth in favor of central counterparties, in the case of a star network (i.e. extreme centralization) counterparty risk is minimized by avoiding excessive exposures among financial institutions –by concentrating counterparty risk in a dedicated financial market infrastructure.

About liquidity risk, we suggest that a complete network is an extreme case of liquidity availability in which all financial institutions have a borrower and lender relationship with each other, therefore minimizing the risk of not finding a counterparty to exchange liquidity with. In this vein, a complete network maximizes bilateral liquidity insurance in the sense of Castiglionesi and Wagner (2013) by reducing the distance between financial institutions. However, by reducing the distance among financial institutions to a minimum, a complete network not only minimizes liquidity risk but also creates counterparty risk by getting all financial institutions closely interconnected.

⁴ Battiston et al. (2012b) and Roukny et al. (2013) tested that risk diversification effects are non-monotonic with respect to connectivity, and that diversification is conditional on the agents' heterogeneity, market liquidity, the size of exogenous shocks, and the cost of credit runs. For instance, based on several configurations, Roukny et al. (2013) tested that in most cases cascade effects under illiquid market conditions are non-monotonically increasing on the number of connections of the network. This contradicts the base case model of Allen and Gale (2000).

As the two extreme cases of network centralization correspond to two particular cases of network optimization in which financial institutions' connections (i.e. network's density) and mutual distances are simultaneously minimized (see Ferrer i Cancho and Solé (2003) and Newman (2010)), we explore how different connective structures yield dissimilar combinations of liquidity risk and counterparty risk. That is, in our case we suggest that there is a direct relation between network's density and counterparty risk, and a direct relation between financial institutions' average distances and liquidity risk. And we suggest that there is an inverse relation between network's density and financial institutions' average distance. This last relation was manifest in global financial crisis of 2007-08 (see Acharya et al. (2012) and Temizsoy et al. (2015)), when surplus banks rationed liquidity amid increased uncertainty about counterparty risk (i.e. reducing density), which resulted in the difficulty of needy banks to access liquidity (i.e. higher average distance), with the consequent intervention of central banks as lenders of last resort to restore access to liquidity (i.e. to reduce average distance).

Our suggested framework is also related to a general case of empirically-consistent social and economic networks formation illustrated by Hojman and Szeidl (2008), in which the benefits of establishing connections exhibits decreasing returns, whereas those benefits decay with network distance. In our case connections' decreasing returns are related to risks, costs, and frictions associated to establishing and maintaining connections (e.g. counterparty risk), whereas network distance is related to how easy it is to find a counterparty to exchange liquidity with.

Our results suggest that different types of money market networks diverge in their centralization according to their main economic features. As expected, by construction, central bank's repo network is a fully centralized star network. Interestingly, the secured liquidity market and the entire money market are more centralized than the unsecured market. About how each market balances counterparty risk and liquidity risk, evidence suggests both secured and unsecured money markets display features consistent with liquidity cross-underinsurance (see Castiglionesi and Wagner (2013)), but they differ in their nature. We also find an inverse and significant relation between counterparty risk and liquidity risk, which differs across markets in an intuitive manner.

To the best of our knowledge this approach to examining the connective structure of financial networks is missing. All in all, our work sheds light on how liquidity exchanges between financial institutions occurs in different types of networks, and on how the tradeoff between liquidity risk and counterparty risk is resolved. As most literature on the ability of different network structures to manage liquidity is of a theoretical nature (see Allen and Gale (2000), Castiglionesi and Wagner (2013) and Castiglionesi and Eboli (2015)), our work provides some empirical ground to the discussion.

One direct implication of our results is that the connective structure of central bank's repo network may be particularly helpful in alleviating tensions in the money market. Thus, we provide evidence favoring the unconventional monetary policy measures adopted by central banks during the global financial crisis. Our results suggest that pledging collateral may grant access to money markets to a wide spectrum of financial institutions that are unable to trade liquidity in unsecured markets, as also reported by Allen et al. (1989) for the United States, presumably due to collateral's role in mitigating problems related to asymmetric information (see Berger et al. (2011)). However, evidence points out that pledging collateral may leave the underinsurance problem unsolved. Finally, our work is relevant to related financial literature because it adds to existing traditional statistics in order to better analyze financial markets. All these are contributions that are important for better understanding financial markets, and as additional tools for policy making.

2 Centralization of networks and the money market

Most research related to centrality in financial networks is devoted to measuring the importance of financial institutions, especially with systemic importance in view (see León et al. (2015)). Nevertheless, financial networks' centralization, corresponding to how centralized financial networks are, is an issue to be addressed by related literature. In this section we first introduce the network's centralization concept and its relation to the well-known centrality concept. Afterwards we substantiate the importance of financial network's centralization for examining and understanding the main structural properties of the money

market and its constituent networks, namely the secured, unsecured and central bank's repo networks.

2.1 Centralization of networks

Centrality is a common concept in network analysis. It is a quantification of how important a participant or vertex is in a networked system, with many possible definitions of importance, and correspondingly many centrality measures (Newman, 2010). Some centrality measures are rather straightforward. For instance, the simplest centrality measure, *degree centrality*, corresponds to the number of connections or edges of a vertex. Some other measures of centrality are increasingly convoluted and aimed at specific purposes or systems, such as *betweenness centrality* (Freeman, 1977), *closeness centrality* (see Newman, 2010), *eigenvector centrality* (Bonacich, 1972), *Katz centrality* (see Newman, 2010), *PageRank* (Brin & Page, 1998), and *hub* and *authority centrality* (Kleinberg, 1998).

Although centrality is commonly circumscribed to the importance of vertexes within a network, there are also centrality measures as a property of the whole network. Correspondingly, Freeman (1977 & 1979) refers to *point centrality* when quantifying the importance of vertexes in a networked system, and to *structural* or *graph centrality* when quantifying how centralized a network is. In the latter case, Freeman suggests that the structural centrality corresponds to measuring the tendency of a single vertex to be more central than all the others (i.e. the dominance of one vertex within the network), in the form of a network's *centralization* index. Accordingly, henceforth we will use centrality when referring to point centrality, and we will use centralization and structural centrality interchangeably.

Ideally, all indexes of network centralization, regardless of the underlying centrality measure, should comply with two features (Freeman, 1979): (i) They should index the extent to which the centrality of the most central vertex exceeds the centrality of all other vertexes, and (ii) they should be expressed as a ratio of that excess to its maximum possible value for a graph containing the same number of vertexes. In this vein, let x be a centrality measure (e.g. degree, closeness); n the number of vertexes; $c_x(v_i)$ the x -centrality of the i -vertex; $c_x(\bar{v})$ the largest value of $c_x(v_i)$ for any vertex in the network; and $\check{C}_{x,n}$ the

maximum possible sum of differences in the chosen x -centrality measure for a network of n vertexes, an acceptable network centralization index (C_x) should be in the following form:

$$C_x = \frac{\sum_{i=1}^n [c_x(\bar{v}) - c_x(v_i)]}{\check{C}_{x,n}} \quad [1]$$

where

$$0 \leq C_x \leq 1$$

The numerator of C_x will determine to what extent the centrality of the most central vertex ($c_x(\bar{v})$) exceeds the centrality of all other vertexes. The denominator ($\check{C}_{x,n}$) will express the numerator as a ratio to the maximum possible value of C_x for a graph containing the same number of vertexes, thus it is bounded to the lower and upper limits 0 and 1, respectively.

Different centrality measures may yield different network centralization indexes. Though, two extreme cases of network centralization have been identified and studied in the literature, namely the *star* (or *wheel*) network and the *complete* network (see Freeman (1977 & 1979), de Nooy et al. (2005), and Everett & Borgatti (2007)). Figure 1 presents these two cases for a nine vertex non-weighted and non-directed graph.

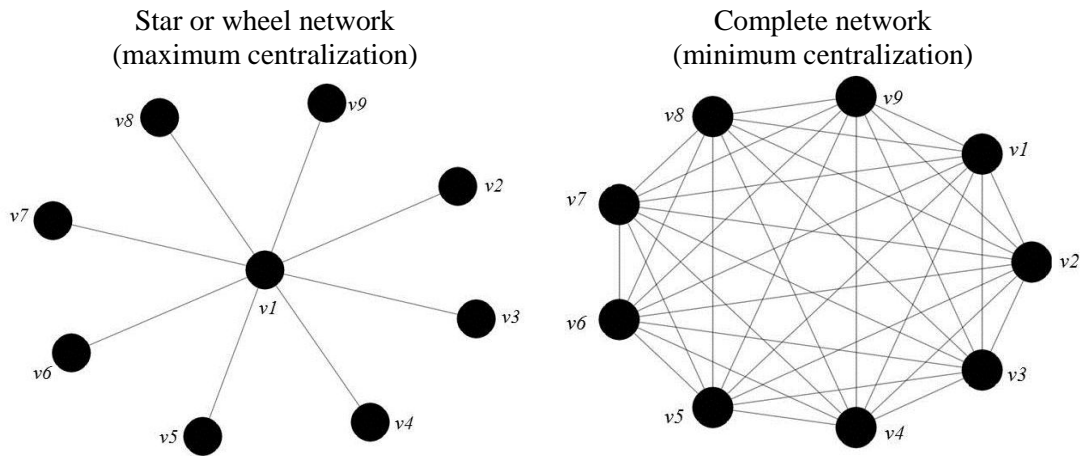


Figure 1. Networks' centralization limit cases for a nine vertex non-weighted and non-directed graph. The star network (left panel) displays the maximum centralization because $v1$ is the sole dominant vertex. The complete network (right panel) has no dominant vertex.

Irrespective of the centrality measure, the highest centralization corresponds to the star network (Figure 1, left panel), in which a single vertex ($v1$) is connected to all other vertexes, which are not connected to each other. Regarding its connective pattern, the ratio of observed edges to possible edges, commonly known as *density* (d), is minimal for a star network.⁵ Furthermore, as its density tends to zero as the number of participants increases, a star network is said to be *sparse* (see Newman (2010)). Also, by construction, the star network has an inhomogeneous distribution of edges, in which all non-dominant vertexes have a single edge, and the sole dominant vertex has $n - 1$ edges. About the shortest number of edges between participants, commonly known as the average path length or average distance (l), it tends to 2 as the number of participants in a star network increases.⁶

On the other hand, the minimal centralization corresponds to the complete network (Figure 1, right panel), in which all vertexes are connected among them.⁷ As all possible edges are present, complete network's average distance between vertexes is the minimum attainable ($l = 1.00$), whereas its density is the highest attainable ($d = 1.00$). The distribution of edges in a complete network is homogeneous: all vertexes have the same number of edges ($n - 1$) and all vertexes are evenly close to each other.

Structural centrality is relevant to the way groups get organized to solve at least some kinds of problems (Freeman, 1979). In some cases, networks are designed specifically to achieve a particular goal, and the structure of the network can heavily influence the efficiency with which that goal is accomplished (Newman, 2010). In this sense, the structure of a network and its centralization may result from an optimization process, by which a tradeoff between conflicting objectives is resolved.

⁵ Density (d) measures the cohesion of the network. The density of a graph with no self-edges is the ratio of actual edges (m) to the maximum number of edges: $d = m/(n(n - 1))$. In the case of star networks $d \rightarrow 0$ as $n \rightarrow \infty$; for each additional vertex there is only one additional edge, but $n - 1$ additional possible edges.

⁶ As in Newman (2010), let g_{ij} be the shortest path (in number of edges) between vertexes i and j , the average path length (l), also known as the mean geodesic distance, corresponds to the mean of l_i over all i -reachable vertexes, $l_i = \frac{1}{(n-1)} \sum_{j(\neq i)} g_{ij}$. In the case of star networks $l \rightarrow 2$ as $n \rightarrow \infty$ because only distances related to the dominant vertex are different from 2.

⁷ An alternative to the complete network as an extreme case of minimal centralization is the circle network (see Freeman (1979)). A circle graph may be constructed by removing non-exterior edges in Figure 1 (i.e. by preserving edges $v1-v2, v2-v3, \dots, v9-v1$). As the density of the star and complete graphs correspond to the two extreme cases of connected networks examined by Freeman, we work with star and complete networks only.

A general case for such network optimization process is presented by Ferrer i Cancho and Solé (2003). This optimization minimizes network's density (d) and the average distance between vertexes (l), which are conflicting objectives by construction. In several types of networks (e.g. transport, distribution, communication) it is natural to minimize the costs related to establishing connections by means of minimizing their number (i.e. networks' density), whereas it is also usual to minimize the distance, time or intermediaries necessary to fulfill the goal of the network.

The tradeoff between these two conflicting objectives often determines network's connective structure and –thus- its centralization. As reported by Ferrer i Cancho and Solé (2003), four non-trivial types of networks are obtained by making linear combinations of d and l in an optimization model: sparse homogeneous networks with evenly distributed edges (i.e. Poisson networks), sparse inhomogeneous networks (i.e. scale-free networks), star networks, and highly dense networks. As it is usual with complex systems, this network optimization is particularly non-linear, with sharp discontinuities (i.e. phase transitions) resulting from continuous changes in the linear combination of d and l .

Regarding the feasibility of the two extreme cases of centralization, it is rather uncommon to find star or complete real networks. As in Barabasi (2003), real networks are not centralized as a star: there are hierarchies of hubs that keep networks together, a heavily connected vertex closely followed by several less connected ones, trailed by dozens of even less connected. On the other hand, complete networks correspond to systems in which every element is connected to each other in a feedback loop, and –thus- they are hopelessly unstable (see Simon (1962) and Anderson (1999)). As put forward by Miller and Page (2007), the adaptive actions of individual agents lead the system away from the critical regimes (i.e. star and complete networks) and more toward what an omniscient designer attempting to balance risk and stability would create.

2.2 Money market network's centralization

Bilateral liquidity transactions between financial institutions in the money market face tradeoffs that may be depicted by an optimization process similar to the one described before. A complete credit network, in which all financial institutions have a borrower and

lender relationship with each other, would maximize the availability of counterparties for exchanging liquidity. As in Castiglionesi and Eboli (2015), absent any cost related to exchanging liquidity among financial institutions, a complete (i.e. decentralized) network is the most efficient network. Thus, minimizing the obstacles to building a decentralized money market network would tend to generate benefits in the form of maximizing bilateral liquidity insurance in the sense of Castiglionesi and Wagner (2013).

However, the distribution of liquidity imposes costs to financial institutions, such as transaction, monitoring, informational, and risk-related costs. These costs turn a complete network into an inefficient one (see Castiglionesi and Eboli (2015)), and may impede a complete money market network from arising. First, repeated interactions with a few counterparties may reduce the costs of information asymmetry (see Afonso et al. (2013)). Second, as the extension of credit is conditional on the assessment of credit worthiness and the establishment of a relationship between a borrower and lender, financial institutions are willing to get into a credit contract only with a few counterparties (Battiston et al., 2012a). That is, counterparty risk and systemic risk, in the form of the costs of non-refunded liquidity and indirect contagion, respectively, deter financial institutions from providing liquidity insurance to all other financial institutions, and creates incentives for a sparse money market network in the form of underinsurance (see Castiglionesi and Wagner (2013) and Castiglionesi and Eboli (2015)). Financial institutions' reluctance to engage in credit exposures immediately after the Lehman Brothers failure (and other crisis events) is a fair example of the inverse relation between counterparty risk and network connectedness.

Other factors –besides transaction and monitoring costs- may turn a complete network into an unlikely connective structure for money markets as well. For instance, as in Allen and Gale (2010), Afonso et al. (2013), and Craig and von Peter (2014), heterogeneity among financial institutions (e.g. different balance sheets, sizes, risk profiles, business lines, specializations, funding needs, cash flows, capital market access, location, conglomerates) may impede complete money market networks from arising. Furthermore, following Assenza et al. (2011) and León and Berndsen (2014), it is likely that financial institutions avoid maximizing linkages due to finite resources (e.g. finite funds, counterparty risk limits), which forces weakening prior interactions in favor of new or better ones.

Conversely, a fully centralized star-shaped network would minimize transaction, monitoring and liquidity costs for the money market as a whole. Minimally connected networks with a star shape are known to be the most efficient structure given a fixed number of links (de Nooy et al., 2005), thus maximizing aggregate welfare because they support trading at the lowest linking cost (Babus, 2012). Correspondingly, as in Castiglionesi and Eboli (2015), the star network achieves the full coverage of liquidity risk for the system with the minimum expected losses (i.e. there are no excessive exposures), hence it is the less inefficient in guaranteeing the coverage of liquidity risk.⁸ However, as being at the center conveys advantages (e.g. collecting intermediation fees, market power, and systemic importance subsidies) and disadvantages (e.g. informational costs), competition for the dominant position may arise. A few financial institutions sharing the advantages and disadvantages of being central could grow a core-periphery network structure.

Such an optimization process, in which there is a minimization of two conflicting objectives, namely liquidity risk and counterparty risk, corresponds to the tradeoff between the risk of being unable to find counterparties willing to provide liquidity and the risk of being unable able to collect liquidity refunds, respectively. This tradeoff, alongside other factors, may explain why the money market network depicts an incomplete market in the sense of Allen and Gale (2000). The result is the incomplete and clustered nature of credit networks (see Battiston et al. (2012b)), prompted by the prevalence of dedicated counterparties in the form of a few repeated interactions between financial institutions (see Cocco et al. (2009), Babus (2012), Afonso et al. (2013), Craig and von Peter (2014), and Temizsoy et al. (2015)).

A precise optimal structure, in the form of a network somewhere between full and null centralization, is elusive. A myriad of possible structures, with very different architectures and centralization levels, is feasible. However, there is already some convergence in recent literature about the sparse and inhomogeneous architecture of observed financial networks, either in the form of a core-periphery (see Craig and von Peter (2014) and in ‘t Veld and

⁸ This is precisely the main argument in favor of using central counterparties in over the counter markets: reducing counterparty risk and other costs (e.g. monitoring) by the interposition of a single participant that settles and clears bilateral exposures between financial institutions.

van Lelyveld (2014)), a scale-free (see Boss et al. (2004) and Soramäki et al. (2007)), or a modular scale-free network (see León and Berndsen (2014)). The well-documented sparseness suggests that financial networks are not complete networks. Also, because there are a few well-connected financial institutions –instead of a single one-, it is reasonable to discard star-shaped networks too. Therefore, financial networks' structural stylized facts suggest that they conform to most real networks, with star or complete networks as unlikely outcomes.

3 The dataset

In spite literature tends to generalize about how bilateral liquidity transactions between financial institutions occur, it is clear that all money market transactions are not the same. Some correspond to secured transactions, in which the lender provides liquidity to the borrower with the refund of the loan being secured by the existence of collateral. Some correspond to unsecured transactions, referred in the Colombian market as interbank funds borrowing, in which the lender provides liquidity to the borrower without any collateral securing the refund of the loan. Secured and unsecured liquidity transactions between financial institutions are the focus of most literature on financial networks.

However, central banks participate in money markets as well. A realistic model of money markets has to take the central bank into account (Georg & Poschmann, 2010). Central banks may be regarded as the most important participants of money markets as their intervention determines the efficient allocation of money among financial institutions (see Allen et al. (2009), Freixas et al. (2011), and Acharya et al. (2012)). Under monetary policy considerations, central banks lend (borrow) to (from) financial institutions in the form of –secured- open market operations. An interesting feature regarding central bank's liquidity transactions is that they constitute a star-shaped network by construction: The central bank will be the dominant vertex (v_I in the left panel of Figure 1), whereas all other financial institutions will connect to each other through the central bank.

In the Colombian case the secured market between financial institutions comprise repos and sell-buy backs (i.e. similar to repos) on sovereign fixed income securities, corporate fixed

income securities, and equity. As of 2014 those secured liquidity transactions' value contributes with about 52.51%, with 98.10% (51.52%) corresponding to sell-buy backs on sovereign fixed income securities (Banco de la República, 2015). Open market operations between financial institutions and the central bank are the second most important source of liquidity in the Colombian money market, contributing with about 43.38% of its value. Consistent with the recent monetary policy stance, all open market operations during 2014 were expansionary repos, consisting of the central bank providing liquidity to financial institutions against collateral. Unsecured liquidity transactions are the third source of liquidity with a contribution about 4.11%. The aggregation of these three types constitutes the Colombian money market, as displayed in Table 1.

| Type | Transaction | Contribution |
|-----------|---|--------------|
| Secured | Sell-buy backs on sovereign securities | 51.52% |
| | Other sell-buy backs | 0.70% |
| | Repos | 0.29% |
| | Open market operations (central bank's repos) | 43.38% |
| Unsecured | Interbank funds | 4.11% |

Table 1. Money market transactions. Sell-buy backs on sovereign securities and open market operations with the central bank are the most contributive sources of liquidity for financial institutions in the Colombian case. Interbank funds is a subsidiary source of liquidity. Based on Banco de la República (2015).

Due to the contribution of each type of liquidity transaction in the Colombian case, our dataset will discard those corresponding to repos and sell-buy backs on corporate fixed income securities and equity, which together represent about 1.00%. Therefore, our dataset focuses on three liquidity transactions: sell-buy backs on sovereign fixed income securities, open market operations, and interbank funds, which contribute with 51.52%, 43.38%, and 4.11% of money market liquidity's value, respectively.

Our dataset consist of consolidated bilateral transactions that occurred between May 2 2013 and October 30 2015 (i.e. 609 days of data). Our dataset comprises the three different types of liquidity transactions that are typical of money markets: secured (72,980 transactions)

and unsecured between financial institutions (16,329 transactions), and secured between financial institutions and the central bank (10,051 transactions). Consolidated transactions in all three markets sum up to 96,874.

As depicted by Martínez and León (2015), the Colombian money market has some unusual features worth highlighting. The contribution of unsecured lending is rather low despite it is open to all types of financial institutions (i.e. banking and non-banking, local and foreign, private and government-owned). Only a fraction of all financial institutions lend and borrow without collateral, and they are all banking institutions. In this sense, following Castiglionesi and Wagner (2013), the Colombian unsecured money market appears to display liquidity cross-underinsurance, in which the existence of potential negative externalities induces market discipline and deters lenders from providing liquidity without collateral.⁹

Consequently, most financial institutions, typically small non-banking institutions, lend and borrow against collateral only, as confirmed by the substantial contribution of sell-buy backs on sovereign securities. Based on anecdotal evidence in the Colombian case, this has been related to local financial institutions' aversion to counterparty risk (Martínez & León, 2015). Furthermore, central bank's open market operations sizeable importance reinforces the argument of liquidity cross-underinsurance in the Colombian case. As also reported by Allen et al. (1989) for the United States, collateral is very important in determining effective access to money markets in the Colombian case.

About the construction of money market networks, we work with adjacency matrices, which are the most common mathematical representation of a network. As reciprocity is by no means warranted between financial institutions, the direction of edges (i.e. from lender to borrower) is relevant, thus we work with directed adjacency matrices.¹⁰ For a system of

⁹ It has been tested that Colombian banking institutions with higher probabilities of becoming insolvent pay significantly more for unsecured funding (see Sarmiento et al. (2015)), which highlights the importance of market discipline (see Furfine (2001)).

¹⁰ For constructing central bank's repo network we assume that an edge from the central bank to a financial institution always implies the existence of an edge from the financial institution to the central bank; that is, we assume reciprocity. By making such assumption we are able to incorporate the role of the central bank in expansionary and contractionary monetary stances, in which it is most plausible that those entitled to access liquidity from the central bank upon pledging collateral are also entitled to lend to it. This assumption not

n participants or vertexes, a directed adjacency matrix A is a square matrix of dimensions $n \times n$, potentially non-symmetrical, with elements A_{ij} such that

$$A_{ij} = \begin{cases} 1 & \text{if there is an edge from } i \text{ to } j, \\ 0 & \text{otherwise.} \end{cases} \quad [2]$$

In our case we do not assign real numbers to the edges; that is, we do not work on weighted adjacency matrices. As we are interested in the connective structure of the network, with all our measures based on the number of edges (i.e. degree centrality and density) or path lengths (i.e. closeness centrality and average distance), working on non-weighted adjacency matrixes is appropriate. The dimensions of each matrix correspond to the number of participants for each market for each date in the sample; that is, n varies throughout the sample in order to reflect the dynamics of financial institutions' access to money markets.¹¹

4 Main results

We present our results in two subsections. First, we examine the main properties of the four markets, with emphasis on their centralization. Second, based on each network's density and average distance, we interpret and analyze how each one of the markets solved the tradeoff between liquidity risk and counterparty risk.

4.1 Main properties of the networks

Some basic network statistics are useful for characterizing each market for the purposes of this paper.¹² The most common have to do with the number of participants in each network,

only allows circumventing the lack of contractionary transactions in the examined period, but it also preserves the analytical soundness and reach of our research.

¹¹ An alternative is to keep the number of participants constant throughout the sample for each market. We tested this alternative and found that it is inconvenient as the density of the matrices is extremely biased to low values because all financial institutions would be expected to participate in the market at all times. Moreover, by using this alternative we would ignore that financial institutions may opt not to participate in the money market.

¹² It is important to highlight that the non-large and disparate number of participants across the networks may complicate their examination by means of the selected basic network statistics: some of them are intended for large networks. For instance, we attempted to estimate the power-law coefficients based on Clauset et al. (2009), but in some cases the number of participants did not allow to do so in a sound manner –thus we decided not to report them. Also, it is important to acknowledge that there are numerous basic statistics useful

its density, the average distance between participants, and network's centralization. We also calculate the assortativity coefficient (see Newman (2010)), which measures how correlated participants are based on their degree (i.e. number of edges).¹³ Table 2 presents these statistics.

| Network Statistic | CB's Repo (<i>CB</i>) | Secured (<i>S</i>) | Unsecured (<i>U</i>) | All Money Market (<i>MM</i>) |
|--|----------------------------|-------------------------|---------------------------|--------------------------------------|
| Number of participants (<i>n</i>) | 17.53 [4.50] | 42.59 [3.42] | 17.59 [2.68] | 52.73 [3.37] |
| Density (<i>d</i>) | 0.13 [0.05] | 0.07 [0.01] | 0.10 [0.02] | 0.06 [0.01] |
| Average distance (<i>l</i>) | 1.88 [0.05] | 2.62 [0.24] | 1.29 [0.23] | 2.63 [0.21] |
| Degree centralization (<i>DC</i>) | 1.00 [0.00] | 0.18 [0.03] | 0.14 [0.04] | 0.14 [0.03] |
| Closeness centralization (<i>CC</i>) | 1.00 [0.00] | 0.46 [0.03] | 0.16 [0.06] | 0.45 [0.03] |
| Assortativity coefficient (<i>r</i>) | -0.21 [0.06] | 0.41 [0.09] | 0.75 [0.11] | 0.45 [0.07] |

Table 2. Mean and standard deviation (in brackets) of selected network statistics. All statistics are calculated on the number participating institutions for each market for each date in the sample (i.e. matrix dimensions varies throughout the sample). Figure 3 (see Appendix) displays time-series plots of selected network statistics.

The average number of participants in each market and its corresponding network shows that central bank's open market operations and the unsecured market are those with less financial institutions, about 17. The secured market, consisting of sell-buy backs between financial institutions with local sovereign securities as collateral, has about 42 participants,

for characterizing financial networks, such as clustering coefficient and diameter –among others; for the purposes of this paper they are not considered as particularly illustrative.

¹³ As usual with correlation measures, the assortativity coefficient (Newman 2010) is bounded to the $[-1, +1]$ interval. A positive correlation corresponds to those cases in which high-degree (low-degree) vertexes tend to be connected to other high-degree (low-degree) vertexes, whereas a negative correlation corresponds to those in which high-degree vertexes tend to be connected to low-degree vertexes. Positive correlation is typical of core-periphery structures, which is a common feature of social networks, whereas negative correlation is typical of star-like networks (see Newman (2010)).

whereas the entire money market has about 52. The average number of participants reveals that the unsecured market is limited to a small group of financial institutions notwithstanding it is open to all of them, whereas the secured displays more than twice the number of participants. It is reasonable that counterparty risk deters most lenders from providing liquidity without collateral (see Martinez and León (2015)), whereas such discriminatory access to unsecured liquidity may be considered a form of underinsurance.

Consistent with literature on financial networks, all four networks are sparse. Sparseness is more acute in the entire money market network, in which only about 6% of potential edges are observed ($d_{MM} \sim 0.06$); put another way, the typical financial institution exchanges liquidity with no more than 3 counterparties from 51 typically available. Similarly, the secured market network displays a low density ($d_S \sim 0.07$), whereas the unsecured and central bank's repo networks have densities about 10% and 13%, respectively. The high degree of sparseness in the four networks confirms that they all considerably diverge from the complete network case.

Under our analytical framework network's sparseness may be interpreted as a signal of financial institutions minimizing expected losses and costs from credit exposures. As d decreases (increases) financial institutions reveal that they are more (less) cautious about counterparty risk exposure. Therefore, observed sparseness suggests that counterparty risk aversion is important in the four networks.

Central bank's repo network displaying higher levels of density is somewhat unexpected. One of the main features of a star network is its ability to connect participants with the minimum density. However, as exhibited in Figure 3a and Figure 3b (see Appendix), the number of participants in central bank's repo network varies throughout the sample and – thus- causes its density to be unusually high when the number of participants drops considerably. Nonetheless, it is important to realize that central banks exchange liquidity pursuant a monetary policy and/or financial stability goal, with counterparty risk arising from lending being a secondary consideration.

It is also rather unexpected to find that unsecured market's density is higher than secured market's. At first it could be interpreted as counterparty risk aversion being higher when

pledging collateral –a counterintuitive finding. Nevertheless, following Martínez and León (2015), it is reasonable to affirm that such contradictory finding arises from the fact that financial institutions regularly exchanging funds in the Colombian unsecured market are banking institutions that may enjoy exclusive access to central bank’s last-resort lending and other too-big-to-fail implicit guarantees. Put another way, the interbank funds market appears to be a smaller ($n_U \sim 17$) and denser ($d_U \sim 0.10$) club in which banking institutions may bilaterally exchange liquidity without pledging collateral, whereas the secured market is a larger ($n_S \sim 42$) and sparser ($d_S \sim 0.07$) group in which all types of financial institutions (i.e. banking and non-banking, small and large) and their dissimilar counterparty risks and features coexist. Such collateral-related discriminatory access to certain money markets is also observed in the United States (see Allen et al. (1989)). Interestingly, concurrent with King (2008), Gorton and Metrick (2012), and Martínez and León (2015), the absolute and relative sparseness of the secured market suggests that pledging collateral does not offset counterparty risk.¹⁴

Average distance (l) measures how close financial institutions are among them. It reflects the global structure of the network, it depends on the way the entire network is connected, and cannot be inferred from any local measurement (Strogatz, 2003). Under our analytical framework the average distance is a measure of how easy it is for a financial institution to find a counterparty to exchange liquidity with based on repeated interactions. For instance, in the complete network case, in which $l = 1.00$ (i.e. all participants are one edge away from each other), all financial institutions have $n - 1$ potential counterparties readily available to exchange liquidity; in this sense, the complete network case is the case of full liquidity cross-insurance. As the level of l increases financial institutions find a lower number of readily available counterparts to exchange liquidity with. In our case, as in Hojman and Szeidl (2008), direct and indirect access between participants generates benefits, with those benefits decreasing with the distance between participants. Consequently, the average distance is a measure of liquidity risk in the corresponding

¹⁴ If collaterals are not ideal (i.e. information-insensitive) in the sense of Gorton and Metrick (2010), concerns about the ability to recover the collateral value arise, and –thus- secured borrowing may not offset counterparty risk in full.

market, namely the risk of not finding a counterparty that is willing to borrow or lend funds based on prior exchange relations.

The lowest average distance corresponds to the unsecured market ($l_U \sim 1.29$), meaning that the typical financial institution is about one edge away from all other financial institutions; that is, most financial institutions in the interbank funds market are connected to most available counterparties. Unusually low distance between financial institutions may be interpreted as evidence against liquidity underinsurance in the unsecured market. However, it is important to realize that discriminatory access to the unsecured market is also a form of underinsurance: non-banking financial institutions, typically smaller and without access to last-resort lending, are precluded from accessing liquidity in the absence of collateral. Such preclusion is not captured by the average distance statistic, but it is critical to understanding liquidity risk across money markets.¹⁵

Secured networks display higher average distances ($l_S \sim 2.62$), which corresponds to average financial institutions being more than two edges away from all others; hence, most financial institutions require one or two intermediaries to connect to all available counterparties. This is counterintuitive when compared to unsecured market's –lower– average distances. It means that pledging collateral results in average participant's lower availability to find counterparties to exchange liquidity with. Again, the discriminatory access to the different money markets explains such striking finding: As the interbank funds market is a smaller and denser club in which banking institutions may bilaterally exchange liquidity without pledging collateral, the average distance between them is lower than that of the secured market –a larger and sparser group of dissimilar financial institutions. In this sense, pledging collateral allows a greater diversity of financial institutions accessing liquidity, which may be related to collateral's role in mitigating the problems related to asymmetric information (see Berger et al. (2011)).

¹⁵ Moreover, as the customary calculation of distance disregards non-reachable participants, absolute values of average distance may be biased downwards. This also explains why a rather sparse network such as the unsecured market ($d_U \sim 0.10$) attains averages distances close to unity. However, this type of inference is common in network analysis, and relative cross-section inferences are still valid. A plausible but unusual alternative is to impose arbitrary distances among non-reachable participants (e.g. infinite, $n + 1$) and to calculate appropriately. As expected, imposing $n + 1$ distances between non-reachable vertexes increased average distances manifestly for all networks but the one corresponding to central bank's repos. Despite these alternative average distances do not conform to typical distances (e.g. $l > 10$) for networks of similar size, most cross-section inferences between non-central bank networks hold (see Figure 4 in Appendix).

Central bank's repo network exhibits a distance corresponding to its star shape ($l_{CB} \sim 1.88$), which results from financial institutions being two edges away by the interposition of the central bank. Nevertheless, by construction, as the central bank is the sole counterparty able to lend or borrow liquidity in this network, the actual average distance should be $\hat{l}_{CB} = 1.00$, which corresponds to the fact that all participating financial institutions are one edge away from accessing central bank's money. However, in order to maintain the consistency in the usage of network statistics, we treat central bank's repo network as usual.

The entire money market network displays an average distance similar to that of the secured market ($l_{MM} \sim 2.63$). As in the case of the secured market, this may be interpreted as the bulk of financial institutions requiring one or two intermediaries to connect to all others, which may in turn reveal that most financial institutions are connected by the interposition of well-connected participants in a sparse network, presumably in a core-periphery structure.

Regarding networks' centralization, we use the two simplest measures of centrality: degree and closeness. As before, degree centrality corresponds to the number of edges as a measure of network importance, whereas closeness centrality corresponds to the inverse of distance as a measure of network importance. As in Freeman (1979), degree centrality is an index of vertexes' potential communication activity, whereas closeness centrality is an index of vertexes' time and cost efficiency in the network.

As previously stated, irrespective of the selected centrality measure, the star is by definition the most centralized network structure, in which a single dominant vertex is connected to all other vertexes, which are not connected to each other. In this sense, as depicted in Table 2, and Figure 3d and Figure 3e (see Appendix), central bank's repo network is the most centralized one, with degree centralization and closeness centralization being at their maximum values (i.e. $DC_{CB} = CC_{CB} = 1.00$). As a star network, central bank's repo network achieves the full coverage of liquidity risk with the minimum expected losses; that is, with the minimal density, all financial institutions have a counterparty to exchange liquidity. It is uncommon to find real networks that conform to the extreme case of centralization in the form of a star network structure (see Barabasi (2003)). In this sense, despite central bank's repo network is a real network, it is evident that its connective

structure is an artifice of financial regulation and policymaking, as it is also the case of central counterparties. Regarding monetary policy, if the central bank's network is the only source of liquidity, the central bank would be able to set the money market interest rate in a direct manner, and monetary policy would be most efficient in terms of attaining a target cost for liquidity. The side effect of such a case would be that gains from market discipline would vanish: there will be no incentives for money market participants to monitor their counterparties.

The other three networks differ from full centralization. The secured market attains degree centralization about 18% of that one of a star network with the same number of participants ($DC_S \sim 0.18$), whereas the unsecured and the entire money market share the same level of degree centralization ($DC_U \sim DC_{MM} \sim 0.14$). About closeness centralization, central bank's repos networks display the highest centralization ($CC_{CB} = 1.00$), followed by the secured market ($CC_S \sim 0.46$), the entire money market ($CC_{MM} \sim 0.45$), and the unsecured market ($CC_U \sim 0.16$).

Both centralization measures suggest that secured, unsecured, and the entire money market networks deviate significantly from the case of full centralization. This also suggests that there is no single participant that concentrates degree and closeness centrality in these three markets, whereas their sparseness suggests that they also deviate from a complete network. It is reasonable to affirm that these three networks have a structure that is between the star and complete networks, with the unsecured standing closer to a complete network.

Interestingly, yet again we find a result that contradicts intuition: the secured market is more centralized than the unsecured market. Literature suggests that trading against collateral should result in direct trading among all financial institutions, resembling an anonymous trading exchange (see Babus (2012) and Afonso et al. (2013)), thus with a rather decentralized network structure. Nonetheless, our results suggest otherwise, and tend to favor the empirical findings of King (2008), Gorton and Metrick (2012), and Martínez and León (2015) about the limits of collateralization for mitigating counterparty risk. Once more, it is reasonable to affirm that such contradiction arises from the unsecured market being a smaller and denser club in which –larger- banking institutions alone may bilaterally exchange liquidity among them without collateral, whereas the secured market is larger and

sparser, with a dissimilar mix of financial institutions (i.e. banking and non-banking, large and small) that may intensify centralization around a small core of financial institutions.

Regarding the assortativity coefficient (see Newman (2010)), which measures how participants tend to associate with others based on the similarity of their degree, we find that the central bank's repo network is the only case that displays a negative coefficient ($r_{CB} \sim -0.21$). A negative coefficient, resulting in *disassortative mixing by degree*, occurs when participants tend to associate with others who have a different degree (i.e. high-degree vertexes tend to connect to low degree ones, and vice versa), and is typical of star-like networks –such as that of central bank's repo network.

On the other hand, all other networks exhibit positive assortativity coefficients (i.e. *assortative mixing by degree*, or *homophily*), which means that high-degree vertexes tend to stick together in a dense core surrounded by a less dense periphery of low-degree vertexes, as in a core-periphery connective structure (Newman, 2010). This is consistent with the average distances of these three networks ($l_U \sim 1.29$, $l_S \sim 2.62$, $l_{MM} \sim 2.63$), which reveal the role of some financial institutions as intermediaries in the core of a core-periphery structure. The unsecured market attains the highest coefficient ($r_U \sim 0.75$). This is expected as the unsecured market portrays a small club of financial institutions that are quite similar to each other (i.e. banking institutions), presumably in a core-periphery structure, as suggested in León et al. (2015). The secured and the entire money market attain positive assortative coefficients as well ($r_S \sim 0.41$, $r_{MM} \sim 0.45$), but they are lower than that of the unsecured market. This means that they also depict a core-periphery connective structure, but it is less marked than that of the unsecured market.

4.2 The tradeoff between liquidity risk and counterparty risk

A simple optimization process that minimizes average distance and density attains the main types of networks, namely sparse homogeneous, scale-free (i.e. sparse inhomogeneous), star, and highly dense networks, as illustrated by Ferrer i Cancho and Solé (2003). In our case, we suggest that the overall structure of money market networks may result from an optimization process by which a tradeoff between minimizing liquidity risk (i.e. average

distance) and counterparty risk (i.e. density) is resolved. Therefore, it is interesting to examine how each network under analysis solves this tradeoff.

Figure 2 presents a scatter plot that exhibits the different combinations of liquidity risk (y-axis) and counterparty risk (x-axis) for each network, for each day in the sample; below the x-axis and to the left of y-axis there is a histogram that compares the distribution of observations for each market.

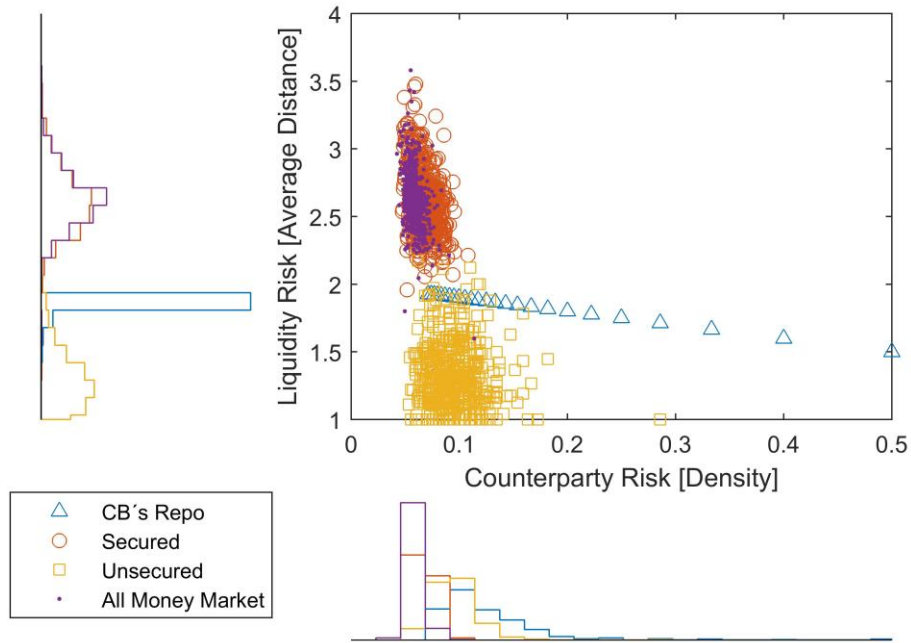


Figure 2. Counterparty risk (x-axis) and liquidity risk (y-axis) tradeoff. Each marker corresponds to the combination between density and average distance calculated on observed daily networks for the four markets.

It is rather clear that each one of the individual markets has a particular combination of liquidity and counterparty risks. For instance, consistent with Table 2, comparing secured (orange circles) and unsecured (yellow squares) reveals that unsecured market's tradeoff involves lower liquidity risk (i.e. lower average distance) and higher counterparty risk (higher density). Again, it is rather counterintuitive to find that unsecured market's density and average distance are higher and lower than those corresponding to secured market's, respectively. Nevertheless, once again, the small club properties of the unsecured market

may explain such result: participants' dissimilar degree of heterogeneity in secured and unsecured markets determines cross-differences in the way they connect among them.

Examining central bank's repo market tradeoff demands caution. It is evident that its combinations yield an intermediate level of liquidity risk, between the unsecured and secured markets. However, as already stated, the actual average distance should be $\hat{l}_{CB} = 1.00$, which corresponds to the fact that all participating financial institutions are one edge away from central bank's money –the only source of liquidity. Central bank's repo networks counterparty risk is the highest and most disperse. This may be interpreted as the central bank being able to accommodate very different network sizes (i.e. number of institutions) and potential costs and losses from non-refunding counterparties without sacrificing its ability to exchange liquidity with the market. Yet, as stated before, the reduced number of participants on certain dates causes the unusual high density in central bank's repo networks (see Figure 3a and Figure 3b in Appendix). After acknowledging the natural limitations of standard network analysis to capture the role of the central bank in the repo network, it is reasonable to affirm that observed network structure and tradeoff conveniently matches central bank's main functions by granting direct access to liquidity without creating excessive exposures between financial institutions –as its star structure allows.

About the entire money market network, most of its combinations of liquidity and counterparty risk overlap with those of the secured market. This is somewhat unexpected because the networks are not weighted, thus the contribution of the secured market is merely structural, and it is not driven by the weight (i.e. value) of its transactions. The combination of liquidity risk and counterparty risk in the entire money market network shows that liquidity risk is higher than that corresponding to the central bank's repo and the unsecured market, and rather similar to that of the secured market. Regarding counterparty risk, consistent with Table 2, the entire money market is particularly sparse. Hence, it is reasonable to affirm that the entire money market network attains a low level of counterparty risk (i.e. low density) and a liquidity risk level close to that attained by the secured market. As both the entire money market network and the secured market network comprise a heterogeneous mix of different types of financial institutions (e.g. banking and

non-banking, large and small), they share a common liquidity and counterparty risks tradeoff, whereas the central bank's repo and the unsecured markets stand because of their particular traits.

Finally, it is interesting to assess the extent to which density explains average distance among financial institutions. To this aim we run a standard linear regression model (ordinary least squares). We expect this linear relation to be inverse (i.e. a tradeoff), with levels varying according to each market's features. Table 3 reports the estimated results. Central bank's repo network is excluded from Table 3 as changes in star-shaped networks' density result in unequivocal and predictable changes in the average distance between participants (i.e. "perfect" regression).

| | Secured (S) | Unsecured (U) | All Money Market (MM) |
|-----------------------|----------------------|----------------------|---------------------------------|
| Density (β) | -9.63 [-10.55***] | -1.06 [-2.45**] | -12.13 [-10.93]*** |
| Constant (α) | 3.26 [52.15***] | 1.39 [32.86***] | 3.34 [51.04***] |
| Adjusted R^2 | 0.15 | 0.01 | 0.16 |

Table 3. Ordinary least squares results. t-statistics are reported in brackets, with statistical significance at 5% (**) and 1% (***). Central bank's repo network is not reported as changes in star-shaped networks' density result in unequivocal and predictable changes in the average distance between participants, thus regression is "perfect" and no errors are available for report or for calculating statistical significance. Estimated coefficients and goodness-of-fit statistics suggest that network's density (d) explains the average distance among participating financial institutions (l), but the explanatory power diverges across markets.

The coefficient corresponding to the secured market displays a significant inverse linear relation ($\beta_S = -9.63$), which reflects that as the network accommodates more linkages (it becomes more dense) the average distance among financial institutions decreases. This means that reductions in financial institutions' counterparty risk aversion (i.e. higher density) should enhance their ability to exchange liquidity (i.e. lower average distance). The goodness-of-fit for the secured market suggests that the model is explanatory to some

extent. Non-linear relations between density and average distance, presumably arising from the way connections are distributed among participants (e.g. clustering, reciprocity), may limit the explanatory power of the model.¹⁶

The coefficient corresponding to the unsecured market displays a negative linear relationship with average distance as well, but the level of the coefficient ($\beta_S = -1.06$) and its significance is lower than that of secured markets. Moreover, the goodness-of-fit for the unsecured markets is rather low, which may be interpreted as other non-considered variables being important for the model. Therefore, the model suggests that increasing the number of connections among financial institutions in the unsecured market does not reduce their average distance as much as in the case of the secured market. As they are quite close already due to their homogeneous features, increasing their interconnections does not affect their ability to find counterparties to exchange liquidity with.

Consistent with the structural resemblance between the secured market and the entire money market, the coefficient for the latter is also significant and its effect is of a similar magnitude ($\beta_{MM} = -12.13$). Therefore, the inverse relation between density and average distance is also apparent after aggregating the three money markets: Variations in the number of connections do affect financial institutions' ability to trade liquidity among them as expected. Not only this matches our expectations, but also overlaps with what was observed during the global financial crisis of 2007-08, when reluctance to engage in exposures (i.e. lower density) resulted in lower access to liquidity (i.e. higher distance), and the subsequent central bank's intervention to restore access to liquidity (i.e. reducing distance).

5 Final remarks

By examining the connective structure of distinct Colombian money market networks we study how financial institutions interact to resolve the tradeoff between liquidity risk and

¹⁶ Market volatility, market liquidity, and central bank's monetary stance –among many others- may be variables to consider in a comprehensive examination of the relation between density and average distance – which is not intended in this paper.

counterparty risk. We undertake this examination by means of measuring money market networks' centralization, and by exploring how centralization is related to attaining two conflicting objectives in network optimization, namely minimizing financial institutions' connections and mutual distances. Based on recent literature on financial networks we assume that these two conflicting objectives correspond to the tradeoff between counterparty risk and liquidity risk, respectively.

To the best of our knowledge this approach to examining the connective structure of financial networks is novel. Therefore, our work provides empirical evidence on how liquidity exchanges between financial institutions occur in different types of money markets, and on how the corresponding distinct liquidity risk and counterparty risk tradeoffs are attained.

Empirical evidence suggests that different types of money market networks diverge in their centralization in an intuitive manner: Central bank's repo network is a fully centralized star network, whereas secured and unsecured liquidity exchanges exhibit features consistent with a sparse connective structure that lays somewhere between the star and the complete network. About how each market balances counterparty risk and liquidity risk, evidence suggests that liquidity exchanges between financial institutions in the unsecured market displays features consistent with cross-underinsurance, which mainly come in the form of a discriminatory access that favors banking institutions. By pledging collateral the secured market allows a broader spectrum of different types of financial institutions to access liquidity, thus reducing cross-underinsurance; this may be related to collateral's role in mitigating problems related to asymmetric information (see Berger et al. (2011)). However, against the intuition that pledging collaterals would yield a dense and well-connected network in which financial institutions could exchange liquidity as in an anonymous trading exchange (see Babus (2012) and Afonso, et al. (2013)), the secured network is sparse and with average distances typical of core-periphery connective structures. In this sense, the secured market also displays features consistent with cross-underinsurance, but in the form of a network with distant counterparties. As expected, central bank's star network achieves the full coverage of liquidity risk with the minimum expected losses, thus

it is the less inefficient in guaranteeing the coverage of liquidity risk (see Castiglionesi and Eboli (2015)).

Implications of our results come in several forms. Our results point out that the connective structure of central bank's repo network may be particularly helpful in alleviating tensions in the money market. Thus, we provide evidence favoring the unconventional policy measures adopted by central banks during the global financial crisis. From our viewpoint, consistent with Acharya et al. (2012) and Temizsoy et al. (2015), central bank's role in most developed countries during the global financial crisis may be portrayed as an attempt to reduce the distance between financial institutions, which had increased amid their reluctance to sustain money markets' connectedness because of a surge in uncertainty about counterparty risk.

Our results also suggest that pledging collateral may reduce cross-liquidity underinsurance by allowing heterogeneous financial institutions to access liquidity from their peers. However, concurrent with other empirical works (see King (2008), Gorton and Metrick (2012), and Martínez and León (2015)), pledging collateral does not offset counterparty risk completely, and does not result in a decentralized network.

Some caveats about our work are worth stating. First, we assume that counterparty risk and liquidity risk may be captured by network's density and average distance. Despite we find this is a fair assumption to make based on related literature, we acknowledge that other institution-centric factors (e.g. robustness, business lines, funding needs, risk profiles, cash flows, location) and system-wide conditions (e.g. market illiquidity, risk aversion, monetary policy stance) may determine the network's connective structure. Examining how those factors may determine the formation of networks is beyond our scope, but it is an interesting research path. Second, a key pending issue in our analysis is related to the recent introduction of mandatory central clearing and settlement for most secured transactions in the Colombian case, namely sell/buy backs with local sovereign securities as collateral.¹⁷ As with other star networks (e.g. central bank's repo network), it is expected that

¹⁷ Starting October 7 2015 it is mandatory that a central counterparty clears and settles all sell/buy backs traded in the electronic trading platform owned and operated by the Central Bank (i.e. SEN). The electronic trading platform owned and operated by the Colombian Stock Exchange (i.e. MEC) adopted central clearing of sell/buy backs on January 18 2016.

centralized clearing and settlement by the sole local central counterparty may contribute to mitigating liquidity risk and counterparty risk. Examining whether (or not) centralized clearing and settlement changes the connective structure of financial institutions' liquidity exchanges in the secured money market is a particularly interesting topic under our approach. Third, estimating the explanatory power of density and average distance as determinants of money market interest rates is worthwhile. They are system-wide measures of market dynamics that may supplement traditional institution-centric determinants (e.g. leverage, solvency, profitability). Finally, as usual with other real-world networks, it is important to highlight that the non-large and disparate number of participants across the networks may complicate their examination by means of basic network statistics, thus conclusions are to be drawn with care.

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7 Appendix

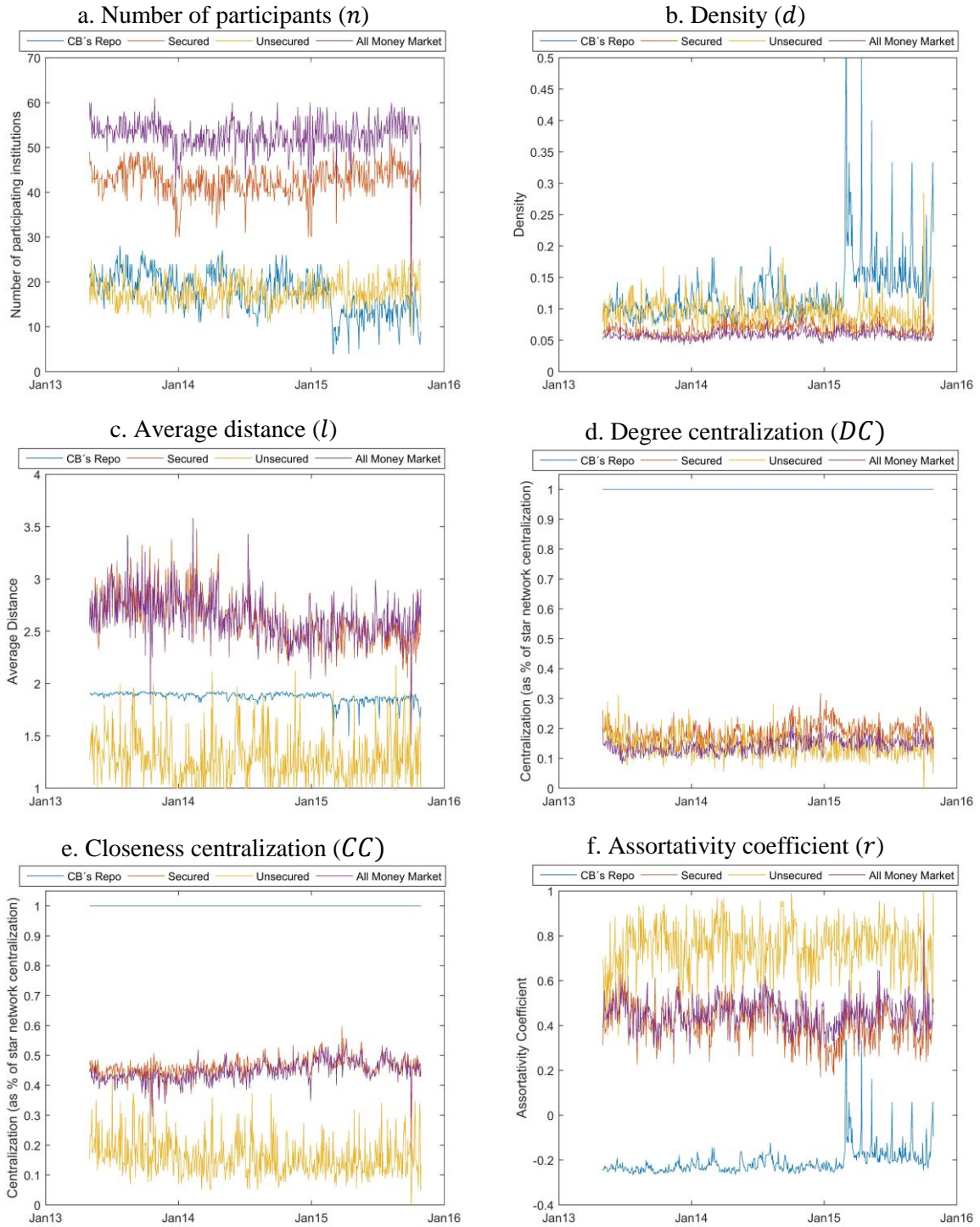


Figure 3. Time-series of statistics in Table 2.

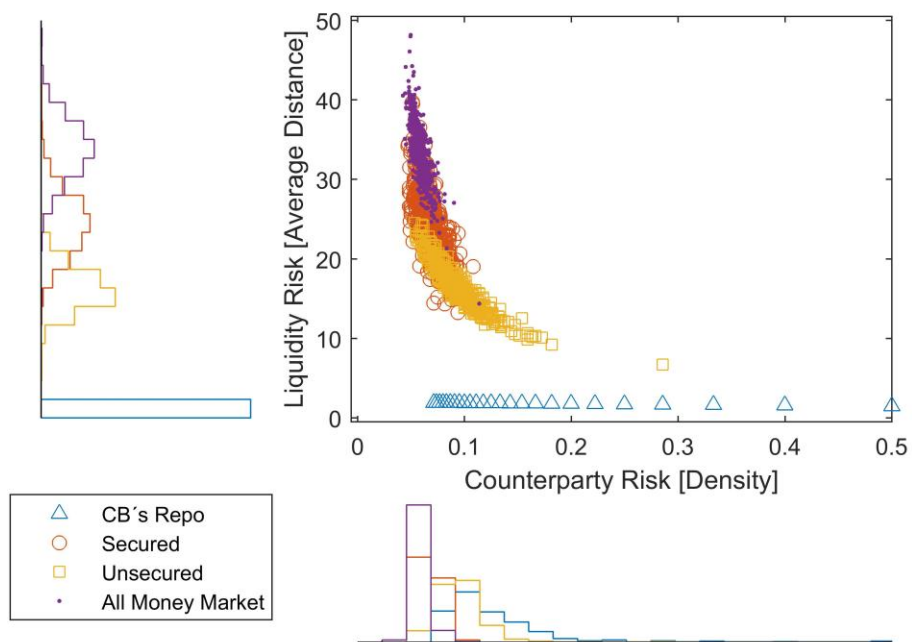


Figure 4. Counterparty risk (x-axis) and liquidity risk (y-axis) tradeoff. Each marker corresponds to the combination between density and average distance calculated on observed daily networks for the four markets. Unlike Figure 2, average distance is calculated for all vertexes (i.e. reachable and non-reachable) by imposing an arbitrary distance of $n + 1$ between two non-reachable vertexes. Consequently average distances increased manifestly in all networks (except that corresponding to central bank's repos).